CUSTOMER-CENTRIC BANK MARKETING STRATEGIES

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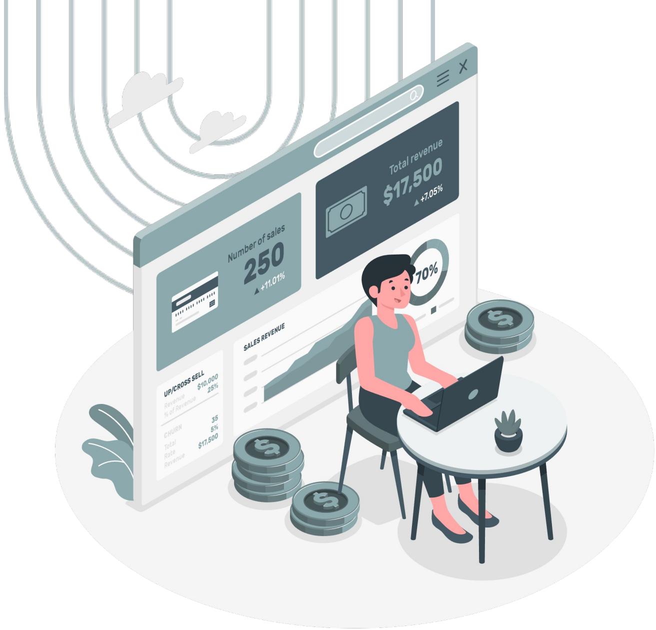


WHY?

Banks interact with a diverse customer base, but traditional segmentation methods based on demographics fail to capture real financial behavior.

WHAT?

- Effective Customer Segmentation
- Targeted Marketing Strategies for Bank Consumers
- Behavior based Approach

ABOUT THE DATA

01. Portuguese Bank's direct marketing campaign (sourced from UCI datasets)

02. May 2008 – November 2010

03. 45,211 observations

04. 17 features (7 numerical & 10 categorical)

05. Demographics, Financial Behavior and Marketing Interaction with the Bank

PATTERNS & TRENDS

Correlation

No strong correlations exist between numeric features directly. Hence, need to uncover underlying patterns through association and clustering.

Engagement

The moderate correlation between p-days and previous suggests that past engagement influences future contact likelihood.

Financials

Median value of yes or no for loans is similar despite balance, suggesting other factors at play for housing loans. But, for personal loans, customers without loans have higher account balances

EDA INSIGHTS

JOB TYPE

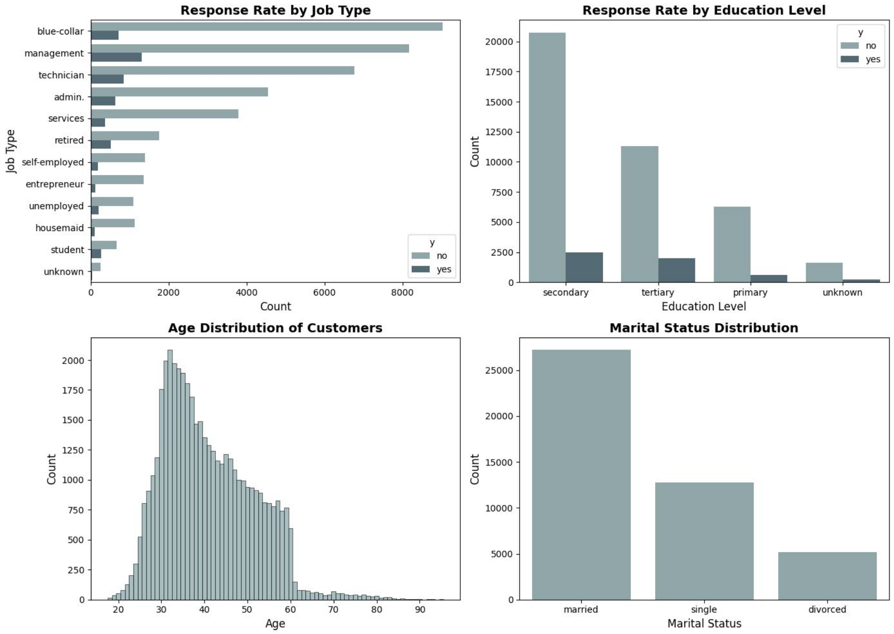
Blue-collar, management, and technician roles dominate, but retired customers show the highest response rates

EDUCATION

Customers with secondary education engage the most but have lower conversion rates, while those with tertiary education are more likely to subscribe

MARKETING

Despite high outreach, subscription rates remain low



30-50 years

Key Age Group

Married

Major share of customers

ANALYSIS

&

INSIGHTS

01.

ASSOCIATION RULE MINING

APPROACH

Why ARM?

Helped uncover hidden relationships in behavior, demographics, past engagement and marketing response

Key Focus

Analyzed how specific attributes affected their responsiveness to marketing outreach

What We Did

Mined patterns in categorical attributes to understand customer engagement drivers

KEY FINDINGS

Customer Engagement

- Cellular contact improved subscription likelihood
- Follow-up calls helped convert hesitant customers

Demographic Patterns

- Education level influenced engagement
- Married customers were less likely to subscribe

KEY FINDINGS

Financial History

- Loan holders were not more or less likely to subscribe
- High-balance customers did not show a strong preference for term deposits

Campaign Impact

- Previous campaign success strongly correlated with future engagement
- Customers who had been contacted multiple times were more likely to respond

STRATEGIES

01. Strengthen follow-up strategies

02. Targeted marketing messaging based on financial literacy level

03. Provide tailored financial products for married customers

04. Leverage past successful engagements

02.

DBSCAN

"Banks overlook their most profitable customers"

WHY DBSCAN?

Unlike K-Means, DBSCAN detects outliers

Model Parameters and Performance

Epsilon (eps): 0.5 (Optimized via K-Distance Graph)

Min Samples: 5 (Prevent underfitting)

Core Cluster Count: 3 main from K-Prototype clustering on top of DBSCAN

FINDINGS

3 main clusters

- Retirees with High Balance
- Moderate balance with Primary and Secondary Education type
- People with Job type Management and Blue Collar jobs

RECOMMENDATIONS TO BANKS

High Balance Retirees

Personalized wealth management services

Blue-collar workers

Low-interest personal loans

“No Jargon" campaigns

To improve accessibility and financial literacy

03.

K-PROTOTYPES CLUSTERING

Why K-Prototypes?

K-Prototypes: Numerical ✅ Categorical ✅
K-Mean : Numerical ✅ Categorical ✖️
K-Mode: Numerical ✖️ Categorical ✅

Workflow

Initializes cluster centroids - Euclidean distance(N) / Hamming(C) ➡️ combination of Euclidean distance ➡️ Assign data points to the closest cluster base on D-function ➡️ Updates cluster centroids iteratively until convergence

The **γ** (gamma) parameter balances the importance of numerical vs categorical data.

$$D(x,y) = \sum(\text{Euclidean Distance for Numerical Data}) + \gamma \sum(\text{Hamming Distance for Categorical Data})$$

K-Prototypes Outcome

What service we need provide to our customer?

High-Risk, Low Balance, Housing Loan Holders	Default Rate: 0.0183 (Highest) Balance: -0.0266 (Lowest) Housing Loan Ownership: 0.8775 Personal Loan Ownership: 0.1214	Offer loan restructuring & financial literacy programs
Moderate Risk, Educated, Loan Holders	Education Level: 1.13 (Highest) Personal Loan Ownership: 0.1455 (Highest)	Promote investment & savings products
Low-Risk, High Balance, Financially Stable	Balance: -0.2278 (Highest) Default Rate: 0.0241 (Lowest) Housing Loan Ownership: 0.9077 (Moderate) Personal Loan Ownership: 0.1423 (Moderate)	Upsell premium banking & investment services

04.

HIERARCHICAL CLUSTERING

Customer Segments Aren't Static – Hierarchical Clustering Captures Their Evolution

Why Hierarchical Clustering?

- Customer behavior is fluid
- Hierarchical clustering allows for evolving segmentation that adapts over time.
- Ward's Method was chosen for best inter-cluster separation & variance minimization.
- This enables banks to track financial transitions & adjust engagement strategies dynamically.

Testing Linkages & Finding the Best Approach

Single Linkage → Overly broad clusters, weak separation.
Complete Linkage → High variance, clusters lacked stability.
Average Linkage → Moderate precision, but weak real-world applicability.
✅ Ward's Method → Best structure, balanced clusters, ideal for financial segmentation.

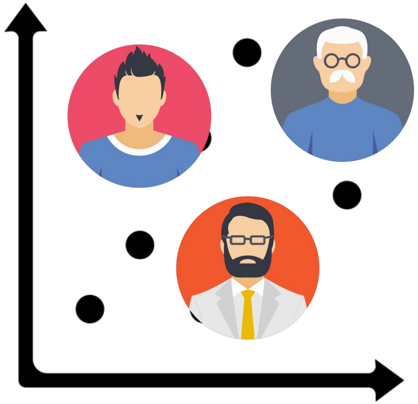
Key Model Performance Metrics:

📊 Cophenetic Correlation: 0.87 (indicates strong hierarchical structure).
📊 Optimal Clusters (K): 3 Determined using dendrogram, silhouette score, Davies-Bouldin Index, and Elbow Method.

✔ Predicts financial transitions → Helps banks anticipate & personalize product recommendations.
✔ Improves long-term customer retention → Enables adaptive engagement strategies.
✔ Optimizes financial product recommendations → Aligns credit, investment, & savings solutions to evolving needs.

Customer Segments Identified:

1️⃣ Young Professionals – Digital banking users, low balances, prefer flexible loans.
2️⃣ Middle-Aged Homeowners – Stable income, moderate engagement, mortgage refinancing candidates.
3️⃣ High-Income Investors – Large balances, prefer wealth management services over standard deposits



How This Helps Banks?

✔ Predicts customer transitions → Track movement between financial categories & personalize offers.
✔ Enhances long-term retention → Recognizing early signs of customer churn or potential upgrades.
✔ Improves financial targeting → Matching the right banking products to evolving customer needs.

📊 Key Business Questions Answered:

Key Business Questions Answered:

1️⃣ How do customers transition between financial behaviors over time?
→ Tracking shifts from young professionals to homeowners allows proactive loan offerings.

2️⃣ Can we identify customers likely to upgrade financial services?
→ Identifying balance growth & spending patterns helps upsell premium services.

3️⃣ How do life stages affect banking product adoption?
→ Major events (e.g., marriage, business, retirement) drive financial decisions.

4️⃣ Which segments are at risk of financial instability?
→ Early detection of declining balances & late payments allows intervention.

5️⃣ What's the best way to retain high-value customers?
→ VIP targeting strategies can ensure wealthier clients stay engaged.

CONCLUSION

Business Recommendations & Conclusions

Key Insights

Financial behavior is a better predictor than demographics.
Past engagement drives future conversions.
Secondary-educated customers engage more but convert less.

Recommendations

Personalized Products → Micro-loans, mortgage refinancing, wealth management.
Targeted Marketing → Prioritize engaged customers, enhance digital outreach.
Optimized Resources → Shift to behavior-driven segmentation, reduce marketing waste.

Conclusion

AI-driven customer segmentation enhances engagement, retention, and revenue growth.

THANK YOU